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The Influence of Non-Cognitive Skills on Wages within and between Firms

Evidence from Bangladesh's Formal Sector

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Abstract

Many employers and employees believe that non-cognitive skills are an important contributor to labor market success. This study has assessed the empirical evidence for such a claim in the case of Bangladesh by evaluating unique employer-employee matched labor market data. The analysis is based on data collected from 6,981 workers in 500 formal sector firms in Bangladesh's five largest formal economic sectors. Using ordinary least squares and firm fixed-effect models, the study assesses correlations between wages and the so-called "big five" personality traits, and augments the analysis with the latent personality scores captured by the Rasch model. Comparing the ordinary least squares and fixed-effect models reveals statistically significant correlations between personality traits and wages, within and across firms. The results appear to indicate that non-cognitive skills are correlated with a worker's likelihood of achieving success in the labor market. Although many of the findings are consistent with the literature, the analysis reveals specific patterns that appear to be unique to Bangladesh, including a positive correlation between "emotional stability" and wages and a negative correlation between "grit" and wages, especially among manufacturing workers. Differences across firms could indicate that firms that offer higher wages may tend to attract workers with distinct types of non-cognitive skills, whereas differences within firms may indicate that variations in non-cognitive skills are associated with disparities in firm-level wage structures. Correlations between wages and personality traits are more prominent among large firms than among small or medium-sized firms.

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The Influence of Non-Cognitive Skills on Wages within and between Firms: Evidence from Bangladesh's Formal Sector[1]

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1. Introduction

It is intuitively logical that non-cognitive skills would affect labor market outcomes. To complete a challenging task on time, workers must be hardworking, committed and punctual, as well as cognitively and technically capable. Traditionally, social scientists have focused on the educational, demographic, and socioeconomic backgrounds of individuals to assess the impact of cognitive skills on wages (Becker, 1964; Mincer, 1974; Card, 2001). Recently, the focus has shifted to measuring cognitive skills through test scores to assess the relationship between cognitive abilities and labor market outcomes (Levy *et al*., 1995; Lee and Newhouse, 2013; Pritchett, 2013). However, in most cases a large amount of the observed variance in wages cannot be explained by cognitive traits alone (Heckman *et al*., 2006).

In this context, studying the economic literature can enhance our understanding of the relationship between non-cognitive skills and labor market outcomes. A diverse range of definitions can be applied to the concept of non-cognitive skills, and different terminologies are often used to describe similar or overlapping concepts, including socioemotional skills, soft skills, non-cognitive skills, character skills, personality traits, 21st century skills, or life skills (Puerta, Valerio and Bernal, 2016). Heckman, Stixrud, and Urzua (2006) introduce psychological variables into their study of social and economic outcomes. Building on the Roy model (1951), they treat non-cognitive skills as endowments and model choices that are determined by non-cognitive skills and other factors as they affect productivity and skills. They find that non-cognitive skills are about equally strong or sometimes stronger predictors of wages, educational attainment, employment status, and choice of occupation, than other factors commonly associated with labor market outcomes.

This analysis examines correlations between non-cognitive skills and wages by using unique employer-employee matched labor market data from Bangladesh. As is consistently argued in the literature, cognitive skills and education levels alone do not fully explain variations in labor market outcomes, and this analysis explores the extent to which non-cognitive skills are correlated with wages. The findings show some association between personality traits, a type of psychological taxonomy comprising of non-cognitive skills, and labor market outcomes in Bangladesh's formal sectors, including a positive correlation between emotional stability and wages. A comparison of

ordinary least squares (OLS) and fixed-effect models using employer-employee matched data shows correlations between personality traits and wages both within and across formal sector firms.

This analysis aims to make three main contributions to the literature on non-cognitive skills and labor market outcomes. First, we present findings regarding the association between personality traits and labor market outcomes among labor force participants in Bangladesh. To the best of our knowledge, this is the first comprehensive assessment of personality traits and their relationship to wages in the South Asian context.[2] With an estimated population of 1.7 billion in 2014,[3] and with the labor force set to grow by 1 million to 1.2 million new workers every month over the next two decades,[4] South Asia presents unique challenges to researchers and policy makers striving to understand the characteristics and skill sets of the region's rapidly growing workforce. Bangladesh presents an especially salient example of the changing employment dynamics in South Asia, as the share of the labor force employed in agriculture shrank from 51 percent in 2000 to 45 percent in 2013.[5] Moreover, the Government of Bangladesh has made skills development a core priority, as described in its 2011 National Skills Development Policy.

Second, we use employer-employee matched data taken from the 2012 Enterprise Skills Survey (ESS), which sampled 500 formal sector employers and employees. Unlike household-based labor force surveys, employer-employee matched data allow an estimation of employee characteristics based on firm-level fixed effects, revealing correlations between different non-cognitive skills and labor market outcomes. Using firm-level fixed effects also reduces the likelihood of omitted variable bias. A comparison of OLS and firm-level fixed-effect models reveals the relationships between wages and personality traits within and across firms.

Third, we compare different methodologies for calculating personality traits. These include a raw index of personality traits and the Rasch rating scale model (Andrich, 1978). The Rasch modeling technique allows us to incorporate latent abilities hidden in the answer patterns for each question and provides a more robust statistical justification for combining various items within the non-

[2] Similar questions were administered in Sri Lanka via the STEP survey (Dundar *et al*. 2014) but we could not find any analysis of the relationship between non-cognitive skills and employment outcomes.
[3] http://data.worldbank.org/region/SAS.
[4] http://blogs.worldbank.org/category/tags/south-asia-workforce.
[5] Bangladesh Labor force surveys.

cognitive skills taxonomy. To the best of our knowledge, this specific methodology for aggregating scores and discovering latent traits has never before been used to assess the so-called "big five" personality traits and their relationship with employment outcomes. While Glewwe *et al*. (2013) also use the Rasch model, they employ a different set of dimensions to measure non-cognitive skills. Similarly, Ajwad *et al*. (2014) and Cunningham *et al*. (2016) use factor analysis to estimate personality traits, while Acosta *et al*. (2015) use simple averages across different categories.

Following this introduction, Section 2 presents an overview of the Bangladeshi labor market and reviews the literature on non-cognitive skills and labor market outcomes. Section 3 describes the data and methodology used to calculate personality trait scores. Section 4 presents the findings of the analysis, and Section 5 discusses these findings and their implications.

2. Literature Review and Background on the Bangladeshi Labor Market

a) *Literature Review*

There is a growing interest in the economic literature in exploring the relationship between non-cognitive skills, or personality traits, and labor market outcomes. Introducing a psychological taxonomy of personality traits has increased the consistency with which non-cognitive skills are defined and measured in the economic literature. The most common form of classification is the so-called "big five" personality traits. These include (i) "openness to experience," (ii) "conscientiousness," (iii) "extraversion," (iv) "agreeableness," and (v) "neuroticism," which can be conversely defined as "emotional stability." This taxonomy represents very broad personality traits, summarizing a large number of distinct and highly specific facets of personality (Almlund *et al*., 2011). While the big five is a commonly used taxonomy, various other measures are also used in different studies (*ibid.*; John and Srivastava, 1999).

The majority of studies that assess the relationship between non-cognitive skills and labor market outcomes focus on developed countries. Using data from Swedish military enlistments, Lindqvist and Vestman (2011) find that non-cognitive skills are a better predictor of employment and annual earnings than cognitive ability. Similarly, using data from the United States, Heckman *et al*. (2011) find that even though non-cognitive skills have little effect on wages after controlling for years of education, they are strong predictors of educational attainment. Carneiro and Heckman (2003) find

that children who received non-cognitive development interventions exhibited greater scholastic and labor market success as adults, even controlling for cognitive abilities.

The World Bank's Skills Toward Employment and Productivity (STEP) Measurement Survey is designed to measure eight personality traits, which include the big five: (i) "extraversion," (ii) "conscientiousness," (iii) "openness to experience," (iv) "neuroticism," (v) "agreeableness," (vi) "grit," (vii) "hostile attribution bias," and (viii) "decision-making style" (Pierre *et al*. 2014), and it has been implemented in developing countries. Several studies have used the STEP taxonomy to test the association between personality traits and labor market outcomes in a developing country setting. In Peru, Cunningham *et al*. (2016) find that perseverance ("grit") and a variable representing both "openness to experience" and "extraversion" correlate closely with some labor market outcomes. Similarly, in Colombia, Acosta *et al.* (2015) find that personality traits have little effect on wages, but play a stronger role in labor market participation.

In Central Asia, Ajwad *et al*. (2014a), using data from the Uzbekistan Jobs, Skills, and Migration Survey, determine that employed workers have better cognitive skills and personality traits than individuals who do not participate in the labor force, and that scores for "decision-making style" are especially low among non-participants. Using the same instrument in the Kyrgyz Republic, Ajwad *et al*. (2014b) find that workers with higher personality trait indicators are also more likely to supervise the work of others, while in Tajikistan Ajwad *et al*. (2014c) find that returning migrant workers have significantly higher cognitive skills and personality trait indicators than non-migrants. In China, using data from the Gansu Survey of Children and Families, Glewwe *et al*. (2013) find that both cognitive and non-cognitive skills strongly influence the decision to stay in school or enter the labor force, with significant differences between boys and girls. Moreover, Chua and Chun (2016) use STEP data to study job and qualification mismatches across different countries.

b) *The Bangladeshi Labor Market*

Bangladesh has made substantial progress in economic and social development in recent decades. Its gross domestic product grew at an average rate of 6.1 percent per year over the past ten years, driving a substantial decline in the poverty rate. With a gross national income of US$1,190 per capita in 2015, Bangladesh is categorized as a lower-middle-income country. Bangladesh's

economic achievements have proven resilient despite its vulnerability to global economic shocks, natural disasters, sporadic bouts of political turmoil, weak governance, and the rising costs of unplanned urbanization.

The country has also made considerable improvements in social indicators, meeting several Millennium Development Goals ahead of schedule. Bangladesh has a large and relatively young population; of 161 million people in 2015, 29 percent were below the age of 15. Each year, 1.3 million young people join the labor force. The poverty rate at the international poverty line decreased from 44.2 percent in 1991 to 33.7 percent in 2000 and 18.5 percent in 2010 (World Development Indicators 2016). Employment is expanding in many of the country's fast-growing economic sectors, including garment production, export-oriented manufacturing, light engineering, shipbuilding, agribusiness, information technology, and pharmaceuticals, and demand for more highly skilled professionals and technical experts is on the rise. However, 89 percent of the labor force is in the informal economy, and a shortage of workforce skills is a major problem (World Bank, 2013). In order to promote the sustainable development of the skilled labor force, it is crucial to understand the skill demands of the formal labor market and the sectors with the greatest growth potential.

3. Data and Methodology

a) Survey Instrument

The data used in this study were collected by the 2012 ESS, which covered employment in the formal labor market only. The survey covered five economic sectors: manufacturing, wholesale and retail commerce, finance, education, and public administration. Together, these sectors employ 91 percent of Bangladesh's formal sector workforce. The survey sample included 6,981 employees at 500 randomly selected enterprises, and the ESS evaluated both their cognitive skills and personality traits (Nomura *et al*., 2013).

b) Hypotheses

The objective of this paper is to analyze the relationship between personality traits and wages by using a unique set of employer-employee matched labor market data from Bangladesh. The

literature consistently finds that cognitive skills and education levels alone do not fully explain variations in labor market outcomes. The analysis is designed to determine whether personality traits are in correlation with wages. In classic human-capital theory, salaries represent the productivity of the individual. Our hypothesis is that non-cognitive skills, as measured by selected personality traits, also play an important part in determining productivity. The analysis compares respondents' wages at the time of the survey with entry-level wages for their respective positions.

c) Estimation of Personality Traits

A diverse range of definitions can be applied to the concept of non-cognitive skills, and different terminologies are often used to describe similar or overlapping concepts, including socioemotional skills, soft skills, non-cognitive skills, character skills, personality traits, 21st century skills, or life skills (Puerta, Valerio and Bernal, 2016). As noted above, this analysis uses the big five personality traits plus measures of grit, hostile attribution bias and decision-making style as in the data collection module developed by the STEP survey (see Table 1 for definitions). All of these traits are independently applied in the literature and are shown to correlate with a range of economic and social outcomes (Pierre *et al*., 2014). The STEP survey estimated each trait through three Likert-style 4-point-scale questions, for a total of 24 questions. The default analytical approach for aggregating the trait scores is a simple average, but a number of other techniques may be applied (*ibid*.). While some studies use the simple average (e.g., Acosta *et al*., 2015), others use factor analysis to recalculate the personality scores (Ajwad *et al*., 2014a, 2014b and 2014c; Cunningham *et al*., 2016).

This study uses an index of personality traits calculated based on the Rasch model rather than on raw personality trait scores. The Rasch model, which is rooted in item-response theory (Rasch, 1960), is commonly used to analyze binary responses. It allows the estimation of latent, rather than observed, scores by applying different weights to different questions depending on relative differences among the sampled respondents. We use a variation of the Rasch model meant to cover categorical Likert-style responses called the rating scale model (RSM), which allows for estimating latent scores in data with non-binary or ordinal variables (Andrich, 1978).[6] For each of

[6] The RSM differs from the partial credit model (PCM), as the latter is also a type of Rasch model used to analyze data with more than two responses. For example, I1 with categories 1-3 and I2 with categories 1-4 can be aggregated

the eight personality trait domains, latent personality trait scores were calculated based on raw item scores.[7]

One of the main advantages of using the Rasch scores, as opposed to raw scores, across items in a single domain is that it allows for estimating latent traits that cannot be captured by raw scores. For example, if certain test questions are more difficult than others, the Rasch model automatically weights the harder questions differently than the easier ones. In the context of personality traits, if certain characteristics are commonly observed in the sample, while other characteristics are rare, Rasch scores are weighted to account for those differences.

Another advantage of the Rasch model is that it objectively justifies the aggregation of different items within a domain based purely on the collected data (Wright and Douglas, 1986). When using raw scores, one can never be fully certain if different questions claiming to measure a certain personality trait are actually doing so until the estimate is justified through a statistical procedure. The Rasch model allows researchers to verify the soundness of grouping multiple questions to calculate one aggregate trait score. While other models, such as factor analysis (Ajwad *et al*., 2014a, 2014b, and 2014c; Cunnigham *et al*., 2016), allow for this as well, the Rasch model was selected for this analysis because of its other advantages and because of the relatively low number of items in each domain.[8] A comparison of standardized distributions between the Rasch model and the raw score model is presented in Figure 1.

d) Employment, Wages, and Other Variables

The ESS survey includes a number of questions on employment and wage-related outcomes. As noted above, entry-level and current wages are our outcome variables, which we convert to log scales to facilitate interpretation. All regressions control for a host of individual characteristics,

using PCM but not RSM. Since all 24 personality trait questions in our data had four uniform responses, namely 1 "Almost Always", 2 "Most of the Time", 3 "Sometimes", and 4 "Almost Never", we use RSM instead of PCM.

[7] We use the RSM package in R, which is a part of the "eRM" library developed by Mair *et al*. (2015) in R. Observations with missing item scores were omitted. The statistical fit of the item in a given domain was checked using the Infit MSQ and Outfit MSQ measures in R. According to the rule of thumb in Rasch literature, Infit MSQ and Outfit MSQ of 0.6-1.4 validate the grouping of items within a single domain (Bradley *et al*., 2006). In our data, three of the 24 items had an Infit/Outfit MSQ < 0.6 (0.58, 0.59). Since these numbers were close enough to the rule of thumb, we decided to keep the items in the domain. Finally, estimated latent scores for each value of the raw score (across items) were calculated using the *person.parameter* function in R.

[8] Factor analysis requires a minimum of three items per domain.

including gender, age, previous work experience, job search duration, employment type, seniority, job type,[9] and geographic area. We also control for cognitive skills as measured by the language (Bangla) and math test scores of workers in the sample. The OLS model also includes control variables for firm size and industry.

e) Estimation Strategy

The analysis is based on an OLS model and a firm-level fixed-effect model. Both models use sampling weights to account for sampling design effects. The OLS model provides correlations between wages and personality traits, which can serve as a basis for comparisons with studies in other countries. They capture the average correlations between wages and personality traits across the sampled firms, controlling for occupation, industries and various individual characteristics.

The firm-level fixed-effect model captures variations within firms. Including firm-level fixed effects eliminates the possibility that differences in form characteristics will compromise the model. The entry-level wage of each worker surveyed in the ESS is modeled by the (1) OLS and (2) fixed-effect regressions as follows:

$$\ln W_i = \beta 0 + \text{Non-cog}_i\, \beta 1 + X_i\, \gamma + \varepsilon_i \qquad (1)$$

$$\ln W_{if} = \beta 0 + \text{Non-cog}_{if}\, \beta 1 + X_i\, \gamma + \alpha_f + \varepsilon_{if} \qquad (2)$$

where W_i is the monthly wage of individual i and W_{if} specifies firm f,
Non-cog_i is one of eight personality traits,
X_i is a vector of covariates that includes individual characteristics, such as age, gender, education level, seniority, employment type, occupation, and industry, as well as cognitive skills as measured by language and math scores,
α_f is the firm-specific constant term in the regression model,
β_0 is a constant reflecting the intercept,
β_1 is the coefficient that measures the returns to personality traits, and
ε_i is the error term for the OLS model and ε_{if} specifies firm f in the fixed-effect model.

[9] Job type is based on the International Standard Classification of Occupations (ISCO).

In the fixed-effect model, standard errors were clustered at the firm level.[10] The main assumption underlying the fixed-effect model is that firm-level characteristics are associated with other independent variables. It is also assumed that unobservable factors affecting both personality traits and outcome variables are firm-invariant.

To fully caveat the shortcomings of the estimation strategy – while both OLS and fixed-effect models control for observables – it may still be subject to bias because of the non-experimental nature of the data. Both the OLS and fixed effect models would overestimate the association between personality traits and wages if an unobservable trait (such as physical complexion) was positively correlated with both personality trait and wages. Similarly, the two models do not show if workers with specific traits select into higher- or lower- paying jobs and firms.

The analysis begins with a model that includes all samples, which is then broken down into three sub-samples based on (i) job type, (ii) industries, (iii) firm size, and (iv) educational attainment in order to assess heterogeneous effects. Job type is defined according to 10 ISCO occupational classifications and aggregated to professional and non-professional groups. The professional group includes ISCO 1-3: (1) managers, (2) professionals, and (3) technicians and associate professionals. The non-professional group includes ISCO 4-10: (4) clerical support workers, (5) service workers, (6) sales workers, (7) skilled agricultural, forestry and fishery workers, (8) construction, craft and related trades workers, (9) plant and machine operators, assemblers, and drivers, and (10) elementary occupations.

4. Results

a) Descriptive Statistics

Tables 2 and 3 present individual-level descriptive statistics of explanatory, exposure and outcome variables. Only 16 percent of respondents were female, reflecting the low female labor-force participation rate in Bangladesh's formal sector. The average age of respondents was 30, and their average job experience (i.e. tenure) was 5 years. Seventy-one percent of respondents worked for firms in Dhaka. Eighty-nine percent of respondents had completed primary school, 32 percent had

[10] Fixed-effect regressions were estimated using the xtreg command in Stata.

completed secondary school, and 22 percent had an undergraduate or graduate degree. These figures reflect the relatively high education level of formal sector workers in Bangladesh relative to the population as a whole. Average language and math scores were 4.74 out of 8 and 5.8 out of 8, respectively, with a standard deviation of 2.62 for language and 2.05 for math. The language and math tests measure a range of primary-level competencies to assess basic cognitive skills. Eighty-nine percent of respondents were permanent employees, 4 percent worked on temporary full-time contracts, and 6.3 percent worked on part-time contracts. Thirty-two percent of respondents were construction and craft workers, 16 percent were clerks, and 13 percent were professionals. Sixty-nine percent of respondents worked for large firms and 67 percent worked in manufacturing. Fourteen percent worked in public administration and 12 percent worked in the education sector.

The average entry-level wage was 5,698 Bangladeshi taka (BDT) per month, and the average current wage was BDT 9,377 per month.[11] Combined with an average of five years of job experience, this indicates that wages grew at a rate of BDT 800 per year. Summary statistics for the standardized Rasch scores, as well as the raw scores for each of the eight personality traits, are also presented in Table 3. Both Rasch scale scores and raw scores were standardized to have a mean of 0 and a standard deviation of 1. Six of the eight personality trait scores (or domains) had three items each, while decision-making style had four items and hostile attribution bias had two. Unanswered items were excluded, and as a result, the sample size for each trait varies.[12]

It is important to note that these personality traits may not remain constant over time. The literature presents mixed conclusions on the persistence of personality traits. Many researchers agree that while personality traits vary over an individual's lifetime, they remain sufficiently stable across situations to confirm their continued existence (Cobb-Clark and Schurer, 2012; Borghans *et al*., 2008; Heckman and Kautz, 2012; Soto *et al*., 2011). There is strong evidence that mean personality

[11] Wage data were converted to a log scale for subsequent regression analysis. By controlling for tenure, relative prices at the time of entry were accounted for in the entry-level wage model.

[12] The sample size varies between 5,304 for "conscientiousness" and 4,385 for "decision-making style." The questions related to decision-making style were placed toward the end of the questionnaire, and some respondents may not have completed the entire set of questions. Unintelligible or clearly false answers were also excluded. The survey contained 752 cases in which the answers of one respondent were identical to those given by at least one other respondent in the same firm. As two or more respondents providing the exact same responses for 24 items is unlikely, these cases were excluded if they occurred within a single firm.

traits change more dramatically between late childhood and adolescence and then vary monotonically and slowly.

Our analysis tested the correlation between personality traits and seniority by running a series of simple regressions (Table 4). The results show that six out of eight traits are not statistically correlated with tenure, but agreeableness and conscientiousness are. This generally allows us to use personality trait scores to review correlations with entry-level wages. For agreeableness and conscientiousness, correlations with tenure are significant at the 10 percent and 5 percent levels. However, since the size of the coefficient is as small as -0.004 and 0.004 standard deviations, respectively, for each additional year of experience, the analysis uses these scores without making any adjustments.

Table 5 shows differences in mean personality traits by gender, education level, industry, job type, and specific occupation. Personality traits vary considerably according to these characteristics. By gender, a statistically significant difference is observed in decision-making style, with male workers tending to apply alternative-solution and consequence-seeking decision making. While there is no statistical difference in personality traits between respondents with no education and those with primary education only, respondents with completed secondary education exhibit significantly higher scores for grit, openness, and hostile attribution bias. Respondents with tertiary degrees score even higher on agreeableness and openness.

Personality trait scores also vary by industry. Compared to manufacturing, respondents working in the commerce sector exhibit higher levels of agreeableness and openness, traits which may be more valuable for customer service. Workers in the education sector exhibit relatively low extraversion scores, and finance professionals exhibit relatively high grit and decision-making scores. Remarkably, public administration professionals and respondents with a tertiary degree exhibit significantly higher-than-average scores across several dimensions of personality, including agreeableness, openness and decision-making style. By occupation, professionals consistently exhibit higher scores for agreeableness, openness, grit, and decision-making style than non-professionals. Scores for agreeableness and decision-making style are lowest among manufacturing workers. These differences by education level, industry, and occupation indicate a need for further analysis of sub-group heterogeneity.

b) Correlation between Personality-Trait Variables

Table 6 presents a correlation matrix for all eight personality-trait variables. The patterns of correlation are generally consistent with the literature, except that higher levels of emotional stability (or lower levels of neuroticism) are somewhat negatively correlated with other big-five traits. Among the big five, extraversion is least correlated with the other four traits, while the other four traits are all positively or negatively correlated with one another. Conscientiousness is positively correlated with emotional stability, agreeableness, and openness. The three other personality indicators, grit, decision-making style, and hostile attrition bias, show broadly similar patterns of correlation. Agreeableness, openness, grit, and decision-making style are closely correlated at between 0.37 and 0.50. However, emotional stability is negatively correlated with all four of these traits. Conscientiousness and extraversion are neutral and show independent correlation patterns with certain other traits.

While these correlations are largely consistent with the findings of the international literature, there are some important contextual variations. The coefficients are generally larger in Bangladesh than in other cases, especially in comparison to a similar study in Colombia (Acosta *et al*., 2015). In Colombia the absolute size of the correlation maxes out at around 0.20, while in Bangladesh it reaches 0.50. Pierre *et al*. (2014) report small to moderate correlations of between 0.1 and 0.4, so Bangladesh may be a unique case in this regard. The direction of the correlation is also unique. A study in Peru finds that all of the big-five traits were positively correlated with each other (Cunningham *et al*., 2016). Such a pattern is also shown by a meta-analysis of 212 psychological studies showing that big-five traits are generally correlated positively with each other (Van der Linden *et al*., 2010). This difference could reflect the specific context of Bangladesh, or it could be attributable to some methodological issue related to the STEP instrument. Other studies indicate that the reliability of the scale might not be very high among countries in the STEP pilot stage because of low literacy rates among respondents, their unfamiliarity with the concepts used in the survey, the presence of reverse-coded items, and the use of a four-point scale for scoring items rather than the original five-point scale (Pierre *et al*., 2014). There is also some debate among researchers regarding the questions used to measure big-five attributes, which are mostly derived from a factor analysis of English words that is translated into other languages, in this case Bengali.

These results should therefore be interpreted with caution, allowing for contextual elements in the data to provide cues (John and Srivastava, 1999; Almlund *et al*., 2011).

c) Estimated Influence of Personality Traits on Wages

We use five different models to analyze and discuss the correlation between personality traits and wages. The first model examines the overall picture by including all respondents in the sample. The second, third, and fourth models analyze specific patterns of correlations by job type, specifically professional versus non-professional workers, and across industries and firm sizes. The fifth model evaluates heterogeneity by educational level. While we mainly use Rasch-scale scores for our outcome variables, we also use raw scores in the first model for comparison. All models use OLS and firm-level fixed effects to compare how personality traits correlate with wages within and between firms, and we run regressions against current and entry-level wage rates.

Table 7 presents the results of the first model, which includes the entire sample. Columns 1-4 show the regression results using Rasch-scale scores, and columns 5-8 show the results using raw scores. The Rasch-scale score model and the raw score model show similar results for both entry-level wages and current wages, as both the size and direction of the coefficients are nearly identical. Most STEP module traits are based on just 3 items, far less than the full big-five inventory instrument, which consists of 44 items for 5 traits. The small difference in the results between the Rasch and the simple average models is thus likely due to the number of items used to construct each of the traits. The Rasch model may be more effective when the number of items is larger. However, due to its ability to calculate latent scores, the Rasch model still represents an improvement. It captures statistically significant correlations between emotional stability and entry-level wages and between agreeableness and current wages in the fixed-effect model, both of which were insignificant in the raw score models. Overall, the results of the Rasch scale and raw score models are broadly consistent, but the Rasch score model may be marginally more effective in explaining the correlations in our case.

The first model reveals certain consistent patterns of correlations between personality traits and wages. Surprisingly, grit is negatively correlated with wages, with slightly larger coefficients in the entry-level wage analysis. This finding may seem counterintuitive, as grit is often thought to contribute to higher wages and greater career success (e.g., Almlund *et al.*, 2011; Cunningham *et*

al., 2016). However, other studies have been unable to find a positive correlation between grit and wages. In Colombia and Uzbekistan, coefficients for grit reveal a statistically insignificant but negative correlation (Acosta *et al*., 2015; Nikoloski and Ajwad, 2014). Given that 67 percent of survey respondents in the current study worked in manufacturing, the results may reflect the unique structure of Bangladesh's formal manufacturing sector. Moreover, the imperfect ability of surveys to capture the dimension of grit is an important caveat. Heckman and Kautz (2012) find evidence of reference bias when survey responses are based on the self-assessments of interviewees. Gerhards and Gravert (2015) find that objectively assessed grit is positively correlated with earnings, whereas self-reported grit is not.[13] However, while self-reporting biases could present an important analytical limitation, we investigate heterogeneity effects in other models before drawing a conclusion.

The analysis also reveals a positive correlation between emotional stability and both entry-level and current wages, as well as a negative correlation between agreeableness and both entry-level and current wages, though only in the firm-level fixed-effect models. While the OLS model shows the average correlation between personality traits and wages for all firms, the fixed-effect model shows wage differentials within firms. Controlling for factors related to the firms themselves, two traits show statistically significant correlations with wages. This suggests that greater emotional stability is not necessarily associated with higher wages in the overall market, but it is associated with higher wages within a given firm when controlling for factors such as occupation type and individual characteristics. Similarly, workers with higher levels of agreeableness tend to receive lower wages than other workers in the same firm when holding all other factors constant. [14]

Finally, the analysis reveals a positive correlation between decision-making style and entry-level wages in the OLS model. This relationship is not apparent in the fixed-effect model, suggesting that while workers with higher decision-making scores are associated with firms offering higher entry-level wages, this relationship does not hold after workers enter a firm or among workers employed by the same firm. This could be interpreted to suggest that individuals who rely on a

[13] Gerhards and Gravert (2015) tested grit by presenting respondents with a mix of hard and easy anagrams and assessing their patterns of skipping or switching to easier anagrams.
[14] The same story from the employers' viewpoint was reported by Kang et al. (2015). They found that more agreeable interviewers are nicer than less agreeable ones to interviewees who ask for more pay.

more alternative or consequence-based decision-making style tend to pursue higher-paying jobs.

The second model analyzes specific patterns of correlations by job type (Table 8). In this model we run regressions using the Rasch scale against subgroups of workers in professional occupations (columns 1-4) and non-professional occupations (columns 5-8) to assess whether the value of personality traits differs by job type. To ensure a large enough sample, the results are not divided by each of the ten ISCO job types, but rather aggregated into two categories—professional and non-professional—with controls for each specific ISCO job type.

The results show a distinct pattern of relationships between professional and non-professional job types. Among professionals, agreeableness is statistically correlated with wages in the fixed-effect model, as in the full-sample model, and no other traits are statistically correlated. Among non-professionals, the analysis shows a negative correlation for grit and positive correlations for emotional stability and decision-making style, which are also consistent with the full-sample model. These results suggest that the statistical correlations found in the full-sample model originate from the correlations between specific traits among professionals and non-professionals. The statistically significant correlation between agreeableness and wages within firms for professional-level workers likely reflects the greater ability of professionals to negotiate their wage rate, and the negative coefficients reflect unsuccessful outcomes of wage negotiations by more agreeable workers. In contrast, emotional stability is particularly important for non-professional workers seeking higher wages. As shown in the fixed-effect model, holding all else constant, workers with greater emotional stability enjoy higher wages. Meanwhile, grittier non-professionals are not as well compensated. Moreover, the analysis finds a positive correlation for hostile attribution bias in the OLS current-wage model.

The third model analyzes specific patterns of correlations by industry (Table 9). Overall, the pattern differs from industry to industry, and no universal trends across industries are observed. Average education levels are lower in the commerce and manufacturing sectors than in education, finance, and public administration,[15] and they employ larger numbers of non-professional workers. As a result, the correlational patterns between traits and wages in the manufacturing sector are

[15] The share of workers with tertiary-level education is 21 percent, 49 percent, 40 percent, 8 percent and 58 percent in commerce, education, finance, manufacturing, and public administration, respectively.

similar to those of non-professionals. In the manufacturing sector, the analysis finds negative coefficients for conscientiousness and grit and positive correlations for decision making and hostile attribution bias in the entry-level-wage OLS model, as well as a positive correlation for emotional stability in the current-wage model. This pattern is broadly consistent with the findings of the first, full-sample model, as well as the findings for non-professional workers in the second model. The correlation between grit and wages in the manufacturing sector appears both in the OLS and fixed-effect models, indicating that this is a relatively robust finding. This suggests that a grittier personality is not necessarily rewarded in Bangladesh's rapidly growing manufacturing sector. The patterns observed in the education sector differ substantially from those in the manufacturing sector. In the education sector, hostile attribution bias is negatively correlated with wages in three specifications. Education is the only sector that shows a negative correlation between hostile attribution bias and wages.

Emotional stability appears to be consistently correlated with wages across sectors, with public administration being the only exception. Emotional stability is positively correlated in at least one specification in the commerce, education, finance, and manufacturing sectors. Agreeableness is positively correlated in two specifications, including the current-wage OLS model in the commerce sector and the entry-level-wage OLS model in the public administration sector. Correlations for extraversion are mixed. A relatively robust and positive correlation between extraversion and wages is observed in the finance sector, implying a positive incentive for finance workers to be extraverted. The results of the OLS model also suggest that a less extraverted person will typically receive a higher entry-level wage in the education sector.

Conscientiousness only appears to be correlated with wages in the entry-level wage model for the manufacturing sector, while openness to experience is not correlated with any industry in any of the specifications. Decision-making style is positively correlated with wages in one specification for the finance and manufacturing sectors, but negatively correlated in fixed-effects models for the commerce sector. The findings for hostile attribution bias are similarly mixed, with positive correlations in the commerce and manufacturing sectors and a negative correlation in the education sector.

This analysis reveals several key features that define the overall relationship between personality traits and wages in Bangladesh's formal sector. First, few traits are universally and consistently correlated with wages. Grit is negatively correlated with wages in the first, full-sample model, but not in the second model for professional workers or in the third model for the commerce, education, and finance sectors. Second, the directions of the coefficients are consistent across the entry-level-wage and current-wage models. Agreeableness and conscientiousness are positively correlated with tenure, and these correlational patterns do not change between the entry-level-wage and current-wage models.

The fourth model analyzes the heterogeneous correlations between personality traits and wages across different firm sizes (Table 10). The results show that correlations between personality traits and wages are predominantly found in large firms. Meanwhile, small firms, with less than 20 employees, and medium-sized firms, with between 21 and 70 employees, do not exhibit strong correlation patterns. A negative correlation between hostile attribution bias and wages seems to be the most common correlation pattern among small and medium-sized firms. In firms with fewer employees, cognitive and technical skills may play a more prominent role than interpersonal skills in determining wage differences.

Workers in large firms are more likely to experience wage differentials based on their personality traits. The general trends observed in the full-sample model, the non-professional model and the manufacturing model are apparent among large firms, including a negative correlation between wages and grit and a positive correlation between wages and hostile attribution bias. Positive correlations for emotional stability in the fixed-effect model and decision making in the OLS model also persist, as well as a negative correlation for agreeableness in the fixed-effect model. From these findings it is clear that labor-market-wide correlation patterns between wages and personality traits are driven by large firms, which employ significant numbers of non-professional workers.

The fifth model examines correlations by education level (Table 11). The descriptive statistics show different patterns of personality traits by educational level, and given that workers from the same education level can be employed in various job types, this set of results provides a complementary picture of the correlations between personality traits and labor market outcomes.

The regression results show distinctive patterns across different education levels. Emotional stability again shows a consistently positive correlation with wages across all levels, but this correlation is most robust among the least-educated workers. This complements the findings that non-professionals and manufacturing workers tend to have better wages when they have higher levels of emotional stability. Other traits show inconsistent patterns. Agreeableness, extraversion, and conscientiousness can be positively or negatively correlated with wages depending on educational level. In this analysis, openness to experience shows a statistically significant positive correlation with wages for the first time among university graduates. While openness to experience is generally uncorrelated with wages, among more educated workers higher levels appear to have positive wage implications.

Grit continues to show a generally negative correlation with wages, and it appears that the negative correlation is especially robust among primary, junior secondary, secondary, and technical and vocational education graduates. In the Bangladeshi labor market, completed primary or secondary education is often effectively a prerequisite for formal employment, and workers with this degree of education are generally low- to mid-level non-professionals and are often employed in the manufacturing sector. Indeed, these findings are consistent with earlier findings for manufacturing workers. Similarly, robust positive correlations are found for decision-making style and hostile attribution bias among secondary and technical and vocational education graduates.

5. Discussion and Conclusion

The literature on labor market outcomes and personality traits is still relatively limited. This paper contributes to that body of literature in several ways. First, data on the relationships between personality traits and labor market outcomes in the South Asia context, and especially in Bangladesh, are rare. This study offers a unique analysis of correlations between personality traits and wages in Bangladesh's formal labor market. Among its key findings is a negative correlation between grit and wages among manufacturing workers and workers with primary and secondary education. This is an interesting pattern that warrants further investigation into the relationship between the formal and informal labor markets in Bangladesh, as well as the effectiveness of the analytical instrument itself. If the observed correlation is accurate, one possible interpretation could be that the negative correlation between grit and wages reflects a unique cultural norm in

Bangladesh or in South Asia more generally. In a comparative study of the organizational culture and human resources practices of Indian and Canadian businesses, Aycan *et al*. (1999) find that Indian employees value paternalistic leadership to a greater extent than Canadians. They also find positive correlations between paternalism and an employee's reactivity and obligation and a negative correlation with proactivity. This type of organizational culture may de-emphasize the importance of grittiness among non-professional workers, who may be expected to be more compliant to the instructions.

Second, by comparing results between the OLS and fixed-effect models the analysis sheds further light on the relationship between productivity and wages in the economic literature. The study uses the firm-level fixed-effect model to control for various factors associated with different economic sectors and firm-level corporate culture and remuneration structures. The OLS and fixed-effect models show distinct patterns in some cases, including a positive correlation for decision-making style in the OLS model, which suggests that individuals with greater decision-making skills and those who apply a more alternative or consequence-based decision-making style tend to pursue higher-paying jobs. Moreover, a positive correlation with emotional stability and a negative correlation with agreeableness in the fixed-effect model suggest that workers with greater emotional stability may be rewarded within their firms, while workers with higher levels of agreeableness may tend to accept lower wages for the same jobs, possibly because they are disinclined to bargain aggressively for higher wages.

Third, by using the Rasch rating scale model, which estimates latent traits, the study provides a more robust justification for personality trait scores. To the best of our knowledge, this methodology has not been previously used to assess big-five personality traits in the economic literature. The analysis shows that there are trivial differences between the coefficients of the Rasch and the simple average models, which is most likely because the number of items per trait is small in the instrument we used. However, we have observed some improvement in the statistical significance of the model.

The analysis reveals several general patterns of association between personality traits and labor market outcomes in Bangladesh's formal sector. First, emotional stability shows a consistently positive correlation with wages across different groups and specifications, while grit shows a

negative correlation, particularly among manufacturing workers and non-professionals. These patterns may reflect Bangladesh's unique corporate management culture, and further investigation into the robustness and accuracy of this finding in both the formal and informal sectors would be worthwhile. Moreover, comparing the results of the OLS and fixed-effect models reveals that correlations between personality traits and wages may appear across firms and/or within firms. Differences across firms could indicate that firms that offer higher or lower wages may tend to attract workers with distinct types of personality traits, whereas differences within firms may indicate that variations in personality traits are associated with disparities in firm-level wage structures. Another interesting finding is that correlations between wages and personality traits are more prominent among large firms than they are among small or medium-sized firms.

While this study provides valuable insights into the influence of personality traits on labor market outcomes, the analysis has important limitations. First, the sample is restricted to the formal sector labor market and focuses on Bangladesh's five largest economic sectors, which together account for 91 percent of the formal labor force. While a better understanding of the factors associated with entry into the formal labor market would be useful to both jobseekers and policy makers, the formal sector represents a relatively small share of Bangladesh's total labor force, as more than 89 percent of workers are employed in the informal sector. Moreover, while the analysis treats personality trait variables with caution when interpreting results, it is difficult to distinguish between the effects of jobseeker preferences and employer demand. The OLS and fixed-effect models show variances in personality traits across firms or within firms, but they do not show whether workers with specific traits tend to seek out higher- or lower-paying firms or whether higher- or lower-paying firms tend to seek out workers with these traits.

Many employers and employees believe that non-cognitive skills are an important contributor to labor market success. This study has assessed the empirical evidence for such a claim in the case of Bangladesh. The results appear to indicate that non-cognitive skills, as measured through personality traits, are correlated with a worker's likelihood of achieving success in the labor market, while the directions of the correlations may be positive or negative depending on the traits as well as on the industry, occupations and size of firms.

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Figure 1: The Distribution of Rasch Scale and Raw Scores by Trait

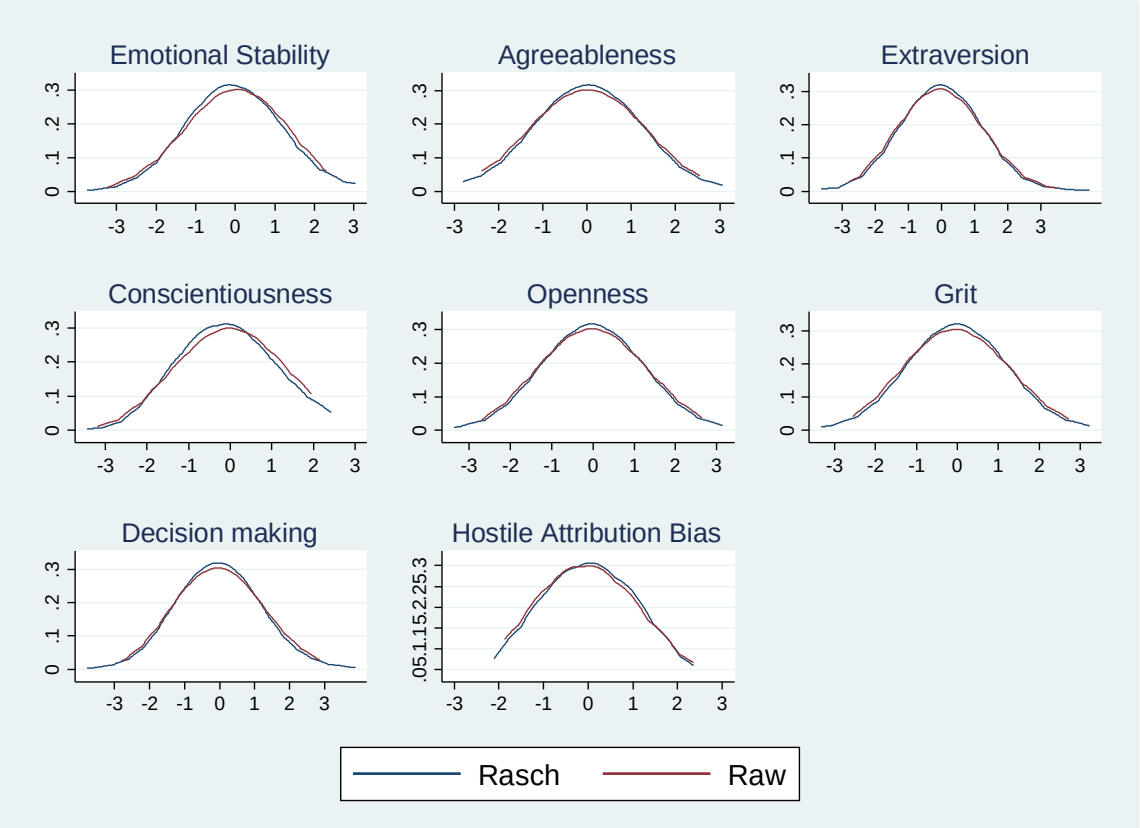

Table 1: Personality Trait Definitions

Traits	Definitions of Traits
Openness to Experience	Big Five: the tendency to be open to new aesthetic, cultural or intellectual experiences.
Conscientiousness	Big Five: the tendency to be organized, responsible and hardworking.
Extraversion	Big Five: an orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience; characterized by positive affect and sociability.
Agreeableness	Big Five: the tendency to act in a cooperative, unselfish manner.
Neuroticism (Emotional Stability)	Big Five: neuroticism represents a chronic level of emotional instability and proneness to psychological distress. Emotional stability, the inverse of neuroticism, is characterized by predictability and consistency in emotional reactions, with the absence of rapid mood changes.
Grit	Trait-level perseverance in the pursuit of long-term goals
Decision making	The score represents the combined effect of two types of decision-making styles: alternative-solution thinking and consequential thinking.
Hostile attribution bias	The tendency to interpret others' behaviors as having hostile intent, even when the behavior is ambiguous or benign.

Source: Adopted from Almund *et al.* (2011) and Pierre *et al.* (2014)

Table 2: Descriptive Statistics with Control Variables

variable	N	mean	sd	min	max
Control Variables					
Female	6981	0.163	0.369	0	1
Age	6981	30.080	8.294	14	71
Years of Experience	6981	5.035	4.964	0	64
Rajshahi	6981	0.063	0.243	0	1
Khulna	6981	0.025	0.156	0	1
Dhaka	6981	0.711	0.453	0	1
Chittagong	6981	0.125	0.330	0	1
Barisal	6981	0.021	0.144	0	1
Sylhet	6981	0.025	0.157	0	1
Rangpur	6981	0.030	0.170	0	1
No education/Incomplete PSC	6981	0.114	0.318	0	1
PSC/JSC	6981	0.348	0.476	0	1
SSC/HSC/TVET	6981	0.317	0.465	0	1
Bachelor/Post Grad	6981	0.221	0.415	0	1
Bangla Test Score	6981	4.737	2.624	0	8
Math Test Score	6981	5.796	2.047	0	8
Previous work experience	6981	0.091	0.288	0	1
Job search duration (log)	6981	1.685	0.890	0	5.3
Emp type= permanent	6981	0.888	0.316	0	1.0
Emp type= contract	6981	0.039	0.193	0	1
Emp type= part time	6981	0.063	0.244	0	1
Emp type= seasonal	6981	0.007	0.085	0	1
Emp type= day laborer	6981	0.003	0.055	0	1
Managers	6981	0.037	0.188	0	1
Professionals	6981	0.134	0.341	0	1
Assoc. Professionals	6981	0.071	0.257	0	1
Clerks	6981	0.155	0.362	0	1
Service Workers	6981	0.093	0.290	0	1
Sales Workers	6981	0.014	0.119	0	1
Skilled Agriculture	6981	0.002	0.046	0	1
Construction Workers	6981	0.322	0.467	0	1
Machine Operators	6981	0.041	0.199	0	1
Elementary Occupation	6981	0.130	0.336	0	1
Firm size: <20	6981	0.153	0.360	0	1
Firm size: 21-70	6981	0.156	0.362	0	1
Firm size: >70	6981	0.691	0.462	0	1
Commerce	6981	0.017	0.129	0	1
Education	6981	0.122	0.327	0	1
Finance	6981	0.054	0.225	0	1
Manufacturing	6981	0.670	0.470	0	1
Pub Admin	6981	0.138	0.345	0	1

Table 3: Descriptive Statistics with Outcome and Exposure Variables

variable	N	mean	sd	min	max
Outcome variables					
Log of Entry Salary	6981	8.441	0.587	5.298	12.10
Log of Final Salary	6981	8.965	0.514	6.215	12.21
Standardized Raw Trait Scores					
Emotional Stability	5097	0.000	1.000	-3.231	2.305
Agreeableness	5018	0.000	1.000	-2.367	2.540
Extraversion	5095	0.000	1.000	-2.762	3.479
Conscientiousness	5304	0.000	1.000	-3.187	1.947
Openness	5265	0.000	1.000	-2.689	2.629
Grit	5250	0.000	1.000	-2.539	2.715
Decision Making	4385	0.000	1.000	-2.786	2.849
Hostile Attribution Bias	4616	0.000	1.000	-1.862	2.359
Standardized Rasch Scores					
Emotional Stability	5097	0.000	1.000	-3.745	3.031
Agreeableness	5018	0.000	1.000	-2.798	3.052
Extraversion	5095	0.000	1.000	-3.623	4.447
Conscientiousness	5304	0.000	1.000	-3.436	2.415
Openness	5265	0.000	1.000	-3.355	3.126
Grit	5250	0.000	1.000	-3.318	3.216
Decision Making	4385	0.000	1.000	-3.777	3.864
Hostile Attribution Bias	4616	0.000	1.000	-2.097	2.357

Table 4: Correlation between Personality Traits Variables and Tenure

	Emotional stability	Agreeable-ness	Extra-version	Conscien-tiousness	Openness	Grit	Decision Making	Hostile Attribution Bias
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tenure	0.001	-0.004*	-0.001	0.004**	0.000	-0.002	0.001	0.001
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	-0.003	0.069***	-0.067***	0.001	0.058***	0.080***	0.040*	-0.012
	(0.020)	(0.019)	(0.020)	(0.019)	(0.021)	(0.019)	(0.022)	(0.021)
Observations	5097	5018	5095	5304	5265	5250	4385	4616
R-Squared	-0.00	0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00
Mean of dependent variable	0.00	0.05	-0.07	0.03	0.06	0.07	0.04	-0.01
Sd of dependent variable	1.03	0.99	1.03	0.99	1.09	1.00	1.04	1.03

* p<0.1; **p<0.05; ***p<0.01

Robust standard errors are shown below the coefficient. Standard errors are clustered at the firm level.

Table 5: Differences in Mean Personality Traits by Gender, Education, and Industry

	Emotional Stability	Agreeable-ness	Extraversion	Conscien-tiousness	Openness	Grit	Decision-making	Hostile Bias
By Gender (Base case is male)								
Female	-0.014	-0.136	0.040	0.067	0.083	-0.154	-0.231**	0.056
	(0.910)	(0.346)	(0.547)	(0.584)	(0.514)	(0.205)	(0.040)	(0.786)
By Education (Base Case is no education)								
PSC/JSC	0.028	0.133	0.023	-0.036	0.026	-0.041	-0.147	0.030
	(0.686)	(0.178)	(0.800)	(0.671)	(0.818)	(0.630)	(0.206)	(0.774)
SSC/HSC/TVET	-0.124	0.125	0.089	0.069	0.182***	0.277***	0.123	0.259*
	(0.386)	(0.277)	(0.376)	(0.560)	(0.006)	(0.001)	(0.254)	(0.050)
Bachelor/Post Grad	0.096	0.277**	0.068	0.175	0.242***	0.141	0.120	0.009
	(0.307)	(0.011)	(0.572)	(0.123)	(0.008)	(0.218)	(0.383)	(0.935)
By Industry (Base case is manufacturing)								
Commerce	-0.016	0.209*	-0.111	0.106	0.302*	0.174	0.197	0.034
	(0.886)	(0.099)	(0.218)	(0.516)	(0.065)	(0.139)	(0.163)	(0.759)
Education	-0.027	0.136	-0.159*	-0.033	0.053	-0.042	0.113	-0.013
	(0.832)	(0.176)	(0.068)	(0.847)	(0.663)	(0.714)	(0.384)	(0.903)
Finance	0.042	0.132	-0.084	0.155	0.195	0.208**	0.330**	0.019
	(0.736)	(0.255)	(0.452)	(0.376)	(0.195)	(0.044)	(0.025)	(0.881)
Pub Admin	0.143	0.339***	0.157	0.261	0.299***	0.105	0.372**	0.098
	(0.345)	(0.008)	(0.253)	(0.199)	(0.008)	(0.566)	(0.018)	(0.397)
By Job Type (Base case is non-professionals, including ISCO4-10)								
Professional	-0.001	0.139**	-0.001	0.046	0.188***	0.194***	0.198***	-0.007
	(0.990)	(0.029)	(0.994)	(0.443)	(0.008)	(0.005)	(0.009)	(0.913)
By Occupation (Base case is construction, craft and related trade workers - ISCO8)								
Managers	0.115	0.263**	-0.198	0.347	0.412***	0.264***	0.491**	0.070
	(0.636)	(0.017)	(0.178)	(0.107)	(0.001)	(0.006)	(0.032)	(0.616)
Professionals	0.011	0.316**	-0.081	0.180	0.235***	0.127	0.407***	-0.020
	(0.936)	(0.013)	(0.478)	(0.247)	(0.003)	(0.213)	(0.000)	(0.869)
Technicians and Associate Profs.	0.009	0.161*	0.071	-0.283**	0.218*	0.264**	0.176	0.059
	(0.932)	(0.071)	(0.679)	(0.041)	(0.090)	(0.039)	(0.140)	(0.669)
Clerical Workers	0.139	0.181*	-0.108	0.097	0.131	-0.028	0.244***	0.007
	(0.332)	(0.093)	(0.303)	(0.612)	(0.195)	(0.862)	(0.006)	(0.956)
Service Workers	0.017	0.251**	-0.078	0.105	0.195*	0.090	0.280**	-0.029
	(0.900)	(0.028)	(0.457)	(0.570)	(0.078)	(0.317)	(0.025)	(0.818)
Sales Workers	0.196	0.109	0.173	0.075	0.150	0.188	0.443***	-0.313
	(0.268)	(0.411)	(0.483)	(0.701)	(0.247)	(0.239)	(0.004)	(0.127)
Agri. Workers	0.183	0.744***	0.035	-0.008	0.404	0.176	0.432*	0.571**
	(0.660)	(0.008)	(0.919)	(0.987)	(0.140)	(0.418)	(0.087)	(0.015)
Plant and Machine Operators, drivers	0.018	0.183	0.009	-0.023	0.194	0.216*	0.331***	0.080
	(0.933)	(0.154)	(0.957)	(0.916)	(0.148)	(0.077)	(0.006)	(0.564)
Elementary Occupations	-0.014	0.234	-0.161*	-0.044	0.051	-0.132	0.286**	0.141
	(0.866)	(0.175)	(0.070)	(0.732)	(0.737)	(0.285)	(0.022)	(0.185)
Observations	5097	5018	5095	5304	5265	5250	4385	4616

* p<0.1; **p<0.05; ***p<0.01

Robust standard errors are shown below the coefficient. Standard errors are clustered at the firm level.

Table 6: Correlation between Personality Trait Variables

	Emotional Stability	Agreeable-ness	Extra-version	Conscien-tiousness	Open-ness	Grit	Decision Making	Hostile Attribution Bias
Emotional Stability	1							
Agreeableness	-0.0839*	1						
Extraversion	-0.00970	-0.0002	1					
Conscientiousness	0.3459*	0.0879*	0.0221	1				
Openness	-0.1050*	0.3754*	-0.0201	0.1501*	1			
Grit	-0.0902*	0.3690*	0.0786*	0.1474*	0.4051*	1		
Decision Making	-0.1275*	0.3946*	-0.00550	0.1093*	0.5022*	0.4140*	1	
Hostile Attribution Bias	-0.3047*	0.2696*	-0.00380	-0.1225*	0.2903*	0.2956*	0.3170*	1

*p<0.05

Table 7: Wage Regression Results, Full-Sample Model

	Rasch Scale				Raw Score			
	Entry Salary		Current Salary		Entry Salary		Current Salary	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Emotional Stability	0.005	0.023*	0.021	0.018**	0.003	0.021	0.019	0.016**
	(0.016)	(0.013)	(0.013)	(0.008)	(0.016)	(0.013)	(0.013)	(0.008)
Agreeableness	-0.036	-0.047*	-0.012	-0.015*	-0.033	-0.044*	-0.011	-0.013
	(0.032)	(0.027)	(0.019)	(0.009)	(0.030)	(0.025)	(0.018)	(0.010)
Extraversion	0.004	-0.009	0.016	0.017	0.002	-0.010	0.016	0.016
	(0.015)	(0.018)	(0.012)	(0.016)	(0.015)	(0.019)	(0.012)	(0.016)
Conscientiousness	-0.018	0.007	0.005	0.000	-0.016	0.006	0.007	0.001
	(0.022)	(0.029)	(0.016)	(0.016)	(0.021)	(0.028)	(0.015)	(0.015)
Openness	0.001	-0.004	0.001	-0.016	0.001	-0.001	0.001	-0.015
	(0.020)	(0.018)	(0.016)	(0.013)	(0.020)	(0.016)	(0.016)	(0.012)
Grit	-0.089***	-0.099**	-0.040**	-0.041*	-0.090***	-0.099**	-0.041**	-0.041*
	(0.023)	(0.049)	(0.017)	(0.024)	(0.023)	(0.048)	(0.017)	(0.023)
Decision Making	0.033*	0.027	0.018	0.020	0.038*	0.029	0.021	0.021
	(0.020)	(0.029)	(0.015)	(0.017)	(0.020)	(0.030)	(0.015)	(0.016)
Hostile Attribution Bias	0.032	0.030	0.022	0.033	0.029	0.027	0.019	0.030
	(0.020)	(0.028)	(0.015)	(0.027)	(0.020)	(0.027)	(0.015)	(0.026)
Constant	8.415***	8.434***	8.679***	8.631***	8.412***	8.433***	8.677***	8.629***
	(0.169)	(0.175)	(0.114)	(0.148)	(0.172)	(0.176)	(0.115)	(0.149)
Observations	2997	2997	2997	2997	2997	2997	2997	2997
R-Squared	0.47	0.42	0.54	0.53	0.47	0.42	0.54	0.53
Mean of dependent variable	8.39	8.39	8.95	8.95	8.39	8.39	8.95	8.95
Sd of dependent variable	0.62	0.62	0.52	0.52	0.62	0.62	0.52	0.52

* p<0.1; **p<0.05; ***p<0.01

Robust standard errors are shown below the coefficient. Standard errors are clustered at the firm level.

Each regression controls for individual characteristics including: gender, age, previous work experience, job search duration, employment type, tenure, geographical division, cognitive test results (literacy, math), industry, and ISCO occupation.

Table 8: Wage Regression Results by Job Type

	Professionals				Non-Professionals			
	Entry Salary		Current Salary		Entry Salary		Current Salary	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Emotional Stability	0.008	0.052	0.017	0.031	0.017	0.039**	0.030**	0.025*
	(0.035)	(0.038)	(0.027)	(0.027)	(0.017)	(0.019)	(0.014)	(0.013)
Agreeableness	0.017	-0.084**	-0.003	-0.054**	-0.050	-0.045	-0.016	-0.011
	(0.034)	(0.039)	(0.029)	(0.026)	(0.038)	(0.036)	(0.022)	(0.011)
Extraversion	-0.014	-0.007	0.022	0.028	0.017	0.005	0.019	0.020
	(0.030)	(0.035)	(0.020)	(0.022)	(0.016)	(0.012)	(0.014)	(0.014)
Conscientiousness	-0.029	-0.013	-0.010	0.003	-0.024	0.006	0.007	0.007
	(0.049)	(0.051)	(0.033)	(0.031)	(0.021)	(0.029)	(0.015)	(0.016)
Openness	-0.034	-0.049	0.002	0.011	0.016	0.018	0.004	-0.017
	(0.037)	(0.040)	(0.029)	(0.028)	(0.022)	(0.018)	(0.018)	(0.014)
Grit	-0.051	-0.025	0.008	-0.024	-0.087***	-0.104**	-0.045**	-0.039*
	(0.040)	(0.048)	(0.029)	(0.031)	(0.026)	(0.049)	(0.020)	(0.023)
Decision Making	-0.003	-0.025	-0.007	-0.025	0.042*	0.041	0.016	0.028*
	(0.035)	(0.032)	(0.028)	(0.023)	(0.022)	(0.027)	(0.016)	(0.015)
Hostile Attribution Bias	0.030	0.034	-0.011	0.000	0.031	0.029	0.037**	0.042
	(0.030)	(0.026)	(0.022)	(0.019)	(0.023)	(0.034)	(0.017)	(0.031)
Constant	8.109***	8.539***	8.151***	8.668***	7.970***	7.830***	8.045***	8.102***
	(0.226)	(0.318)	(0.165)	(0.195)	(0.173)	(0.173)	(0.118)	(0.105)
Observations	920	920	920	920	2077	2077	2077	2077
R-Squared	0.36	0.36	0.42	0.27	0.44	0.26	0.42	0.36
Mean of dependent variable	8.79	8.79	9.40	9.40	8.26	8.26	8.80	8.80
Sd of dependent variable	0.69	0.69	0.55	0.55	0.53	0.53	0.41	0.41

* p<0.1; **p<0.05; ***p<0.01

Robust standard errors are shown below the coefficient. Standard errors are clustered at the firm level.

Each regression controls for individual characteristics including: gender, age, previous work experience, job search duration, employment type, tenure, geographical division, cognitive test results (literacy, math), industry, and ISCO occupation.

Table 9: Wage Regression Results by Industry

	Commerce				Education				Finance			
	Entry Salary		Current Salary		Entry Salary		Current Salary		Entry Salary		Current Salary	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Emotional Stability	0.041	0.038	0.037	0.067***	0.007	0.047*	0.015	0.051***	0.055*	-0.010	0.031	0.001
	(0.033)	(0.026)	(0.024)	(0.021)	(0.034)	(0.028)	(0.026)	(0.018)	(0.032)	(0.034)	(0.023)	(0.028)
Agreeableness	0.042	-0.013	0.044*	-0.007	-0.034	-0.001	-0.054	-0.030	-0.028	0.001	-0.009	0.001
	(0.032)	(0.031)	(0.026)	(0.025)	(0.045)	(0.052)	(0.034)	(0.033)	(0.038)	(0.025)	(0.028)	(0.026)
Extraversion	0.036	0.040	-0.029	0.006	-0.081***	-0.058	-0.020	0.020	0.056*	0.019	0.053**	0.043***
	(0.028)	(0.030)	(0.022)	(0.023)	(0.030)	(0.038)	(0.021)	(0.023)	(0.029)	(0.028)	(0.021)	(0.015)
Conscientiousness	-0.007	-0.016	0.016	-0.010	-0.037	-0.016	-0.025	-0.031	0.022	-0.009	0.002	-0.015
	(0.030)	(0.024)	(0.023)	(0.018)	(0.035)	(0.039)	(0.030)	(0.027)	(0.037)	(0.041)	(0.024)	(0.029)
Openness	-0.029	-0.028	-0.007	-0.021	0.046	0.044	0.010	-0.010	-0.020	0.002	0.005	0.006
	(0.022)	(0.020)	(0.022)	(0.025)	(0.037)	(0.037)	(0.030)	(0.025)	(0.029)	(0.020)	(0.029)	(0.017)
Grit	0.002	-0.001	0.006	0.008	0.017	0.010	0.043	0.013	0.036	0.024	0.001	0.006
	(0.029)	(0.025)	(0.027)	(0.028)	(0.048)	(0.043)	(0.039)	(0.023)	(0.034)	(0.032)	(0.025)	(0.028)
Decision Making	-0.010	-0.048*	-0.019	-0.049**	0.011	-0.039	0.044	0.010	0.044	0.077**	0.030	0.037
	(0.031)	(0.026)	(0.025)	(0.023)	(0.046)	(0.041)	(0.038)	(0.022)	(0.036)	(0.030)	(0.032)	(0.031)
Hostile Attribution Bias	0.051*	0.018	0.053**	0.026	-0.086**	-0.070*	-0.065**	-0.039	0.012	0.002	-0.004	-0.003
	(0.029)	(0.032)	(0.025)	(0.026)	(0.040)	(0.041)	(0.033)	(0.036)	(0.042)	(0.031)	(0.026)	(0.021)
Constant	7.872***	8.586***	8.251***	8.817***	8.963***	8.317***	9.016***	8.124***	8.871***	8.171***	8.489***	8.341***
	(0.210)	(0.165)	(0.177)	(0.146)	(0.281)	(0.237)	(0.196)	(0.172)	(0.450)	(0.458)	(0.241)	(0.286)
Observations	395	395	395	395	472	472	472	472	396	396	396	396
R-Squared	0.52	0.53	0.55	0.55	0.46	0.50	0.42	0.54	0.27	0.37	0.50	0.54
Mean of dependent variable	8.52	8.52	8.97	8.97	8.35	8.35	8.91	8.91	8.65	8.65	9.26	9.26
Sd of dependent variable	0.57	0.57	0.51	0.51	0.65	0.65	0.47	0.47	0.66	0.66	0.50	0.50

* p<0.1; **p<0.05; ***p<0.01

Robust standard errors are shown below the coefficient. Standard errors are clustered at the firm level.

Each regression controls for individual characteristics including: gender, age, previous work experience, job search duration, employment type, tenure, geographical division, cognitive test results (literacy, math), industry, and ISCO occupation.

	Manufacturing				Public Administration			
	Entry Salary		Current Salary		Entry Salary		Current Salary	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Emotional Stability	0.010	0.028	0.029*	0.015	-0.035	0.005	0.001	-0.001
	(0.019)	(0.017)	(0.017)	(0.012)	(0.036)	(0.050)	(0.020)	(0.021)
Agreeableness	-0.047	-0.048	-0.008	-0.013	0.087**	0.038	0.013	0.030
	(0.036)	(0.030)	(0.021)	(0.009)	(0.042)	(0.037)	(0.026)	(0.025)
Extraversion	0.026	0.011	0.019	0.019	-0.045	-0.038	0.019	-0.002
	(0.017)	(0.018)	(0.015)	(0.017)	(0.032)	(0.038)	(0.018)	(0.022)
Conscientiousness	-0.047*	-0.011	0.001	-0.001	0.068	0.033	0.007	-0.012
	(0.026)	(0.040)	(0.019)	(0.023)	(0.043)	(0.042)	(0.022)	(0.021)
Openness	0.013	-0.007	0.007	-0.020	-0.064	0.012	0.013	0.025
	(0.028)	(0.027)	(0.023)	(0.019)	(0.042)	(0.036)	(0.027)	(0.028)
Grit	-0.111***	-0.119**	-0.048**	-0.044	-0.076**	-0.019	-0.048**	-0.041
	(0.027)	(0.050)	(0.021)	(0.027)	(0.032)	(0.032)	(0.023)	(0.026)
Decision Making	0.045*	0.035	0.019	0.017	0.010	-0.010	-0.034	-0.004
	(0.023)	(0.030)	(0.018)	(0.018)	(0.040)	(0.031)	(0.027)	(0.027)
Hostile Attribution Bias	0.039*	0.045	0.030*	0.043	0.028	0.013	-0.014	-0.014
	(0.023)	(0.033)	(0.018)	(0.031)	(0.035)	(0.035)	(0.022)	(0.027)
Constant	8.235***	8.362***	8.652***	8.615***	8.843***	9.315***	8.651***	8.852***
	(0.181)	(0.214)	(0.132)	(0.151)	(0.344)	(0.360)	(0.227)	(0.250)
Observations	1229	1229	1229	1229	505	505	505	505
R-Squared	0.52	0.45	0.55	0.58	0.61	0.58	0.69	0.51
Mean of dependent variable	8.35	8.35	8.88	8.88	8.55	8.55	9.35	9.35
Sd of dependent variable	0.56	0.56	0.49	0.49	0.90	0.90	0.64	0.64

* p<0.1; **p<0.05; ***p<0.01

Robust standard errors are shown below the coefficient. Standard errors are clustered at the firm level.

Each regression controls for individual characteristics including: gender, age, previous work experience, job search duration, employment type, tenure, geographical division, cognitive test results (literacy, math), industry, and ISCO occupation.

Table 10: Wage Regression Results by Firm Size

	Small Firms (<=20 employees)				Medium Firms (21-70 employees)				Large Firms (71+ employees)			
	Entry Salary		Current Salary		Entry Salary		Current Salary		Entry Salary		Current Salary	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Emotional Stability	-0.004	0.013	0.03	0.03	-0.001	0.001	0.004	0.019	0.008	0.031*	0.025	0.017
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Agreeableness	-0.004	-0.015	-0.02	-0.03	0.021	0.014	0.02	0.023	-0.05	-0.050*	-0.013	-0.016
	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.01)
Extraversion	-0.061**	-0.047	-0.019	0.013	-0.005	-0.008	0.004	0.002	0.017	-0.003	0.023	0.018
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Conscientiousness	-0.019	-0.002	-0.029	-0.034	0.015	-0.005	-0.002	-0.015	-0.04	0.002	0.005	0.007
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)
Openness	0.021	0.019	-0.012	-0.009	-0.013	0.029	0.017	0.021	0.002	-0.013	0.003	-0.025
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Grit	0.018	-0.022	0.019	0.001	-0.027	0.004	-0.009	-0.01	-0.115***	-0.123**	-0.049**	-0.047*
	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)
Decision Making	-0.008	-0.029	0.014	0.005	-0.012	-0.042	0.001	-0.008	0.056**	0.045	0.025	0.022
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Hostile Attribution Bias	-0.042	-0.04	-0.068***	-0.032	-0.036*	-0.046**	-0.02	-0.038**	0.059**	0.061*	0.052***	0.061**
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Constant	8.658***	8.983***	8.699***	8.709***	8.790***	8.543***	8.751***	8.711***	8.357***	8.457***	8.795***	8.727***
	(0.19)	(0.22)	(0.13)	(0.15)	(0.18)	(0.23)	(0.13)	(0.14)	(0.23)	(0.22)	(0.16)	(0.17)
Observations	687	687	687	687	903	903	903	903	1407	1407	1407	1407
R-Squared	0.41	0.46	0.48	0.52	0.45	0.42	0.54	0.46	0.56	0.46	0.63	0.59
Mean of dependent variable	8.34	8.34	8.89	8.89	8.39	8.39	9.02	9.02	8.4	8.4	8.94	8.94
Sd of dependent variable	0.63	0.63	0.48	0.48	0.66	0.66	0.5	0.5	0.61	0.61	0.53	0.53

* p<0.1; **p<0.05; ***p<0.01

Robust standard errors are shown below the coefficient. Standard errors are clustered at the firm level.

Each regression controls for individual characteristics including: gender, age, previous work experience, job search duration, employment type, tenure, geographical division, cognitive test results (literacy, math), industry, and ISCO occupation.

Table 11: Wage Regression Results by Education Level

	Non-Educated, Incomplete Primary				Primary or Junior Secondary				Secondary, TVET				University, Post-graduate			
	Entry Salary		Current Salary		Entry Salary		Current Salary		Entry Salary		Current Salary		Entry Salary		Current Salary	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Emotional Stability	0.101***	0.099***	0.083***	0.034**	0.021	0.038	-0.002	0.013	-0.007	0.015	0.024	0.029**	0.038	0.04	0.047*	0.033
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.04)	(0.04)	(0.03)	(0.03)
Agreeableness	0.012	0.031	-0.040*	-0.004	-0.027	-0.021	0.006	0.025*	-0.07	-0.077**	-0.003	-0.004	0.012	-0.052	-0.026	-0.014
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.01)	(0.05)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
Extraversion	-0.018	-0.001	-0.039**	-0.025**	0.033	0.014	0.026	0.019	0.007	0.001	0.023	0.041*	-0.041	-0.047	0.009	0.021
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)
Conscientiousness	0.004	-0.011	0.035**	-0.023	-0.035	-0.008	0.012	0.025	-0.021	-0.001	-0.017	-0.021	-0.077***	0.038	-0.025	0.028
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)
Openness	-0.006	-0.018	-0.021	-0.033*	0.033	0.011	0.01	-0.016	-0.02	-0.009	-0.004	0	0.042	0.056*	0.070***	0.052**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Grit	0.033	0.033	0.022	0.043**	-0.115***	-0.123**	-0.041	-0.029	-0.088***	-0.133***	-0.058**	-0.067***	-0.033	0.016	0.021	-0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)
Decision making	-0.022	-0.015	-0.007	-0.01	0.063**	0.03	0.027	0.03	0.066**	0.065*	0.018	0.018	-0.029	-0.039	-0.033	-0.039
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Hostile attribution bias	-0.027	-0.025	0.041**	0.014	-0.011	-0.005	-0.011	0.001	0.087**	0.098**	0.055**	0.069*	-0.002	-0.009	0	-0.008
	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.04)	(0.03)	(0.02)	(0.03)	(0.02)
Constant	8.385***	8.426***	9.017***	8.701***	8.177***	8.158***	8.671***	8.586***	8.385***	8.029***	8.541***	8.347***	9.247***	9.251***	9.036***	9.190***
	(0.25)	(0.24)	(0.20)	(0.18)	(0.17)	(0.18)	(0.15)	(0.14)	(0.25)	(0.36)	(0.20)	(0.23)	(0.29)	(0.38)	(0.21)	(0.28)
Observations	467	467	467	467	901	901	901	901	936	936	936	936	693	693	693	693
R-Squared	0.6	0.41	0.56	0.34	0.44	0.22	0.37	0.35	0.43	0.42	0.44	0.55	0.45	0.46	0.5	0.33
Mean of dependent variab	8.13	8.13	8.63	8.63	8.19	8.19	8.71	8.71	8.41	8.41	9.00	9.00	8.91	8.91	9.49	9.49
Sd of dependent variable	0.57	0.57	0.41	0.41	0.49	0.49	0.39	0.39	0.55	0.55	0.43	0.43	0.68	0.68	0.52	0.52

* p<0.1; **p<0.05; ***p<0.01

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Each regression controls for individual characteristics including: gender, age, previous work experience, job search duration, employment type, tenure, geographical division, cognitive test results (literacy, math), industry, and ISCO occupation.